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DELAY-SENSITIVE APPLICATIONS IN UBIQUITOUS VEHICULAR SYSTEMS

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ABSTRACT
The modern context of the transport infrastructure is witnessing the adoption of Intelligent Transportation Systems (ITS). These systems have enabled real-time decision-making and intelligent mobility in conjunction with vehicle infrastructure systems. Urgent applications, such as Autonomous Vehicle Maneuvering, Automated Collision Emergency Alerts, Real-time video surveillance, and Dynamic Signal Control (DSC), require unparalleled communication speed and maximum processing power. Failure to resolve these issues will impede the prevention of road perils, massive traffic blockages in densely populated areas, and disruption of urban life. Addressing the minimal attainable delay, tailoring individual requirements, is another obstacle that needs to be addressed in the highly volatile network, with stochastic traffic conditions, on-board processing capabilities, and numerous other technical constraints. The goal of this research work is to provide an in-depth analysis of a structure that aims to resolve these constraints through driving scenarios, subject to limitations about the available technology and the extreme requirements of latency. A new integrated framework is presented to address these issues by incorporating edge computing, adaptive data packet prioritization, and contemporary communication protocols, which facilitate prompt communication among vehicles connected to the network. Through system architecture, process flow diagrams, and calculations with defined latency for severe delay conditions, heuristic analytical simulations that employ realistic vehicular datasets validate the framework's capability for improved delay refinement, marking an enhancement over existing methodologies. Furthermore, the Austro control structures for urban traffic management systems validate the frameworks from a practical standpoint. Research indicates that managing the sensitivity of delays to an appropriate level is attainable and highly beneficial for the development of future vehicle networks.
Keywords: Delay-Sensitive Applications, Ubiquitous Vehicular Systems, Edge Computing, Real-Time Protocols, Autonomous Vehicles, Latency Management, Traffic Control

1. INTRODUCTION

1.1 Definition and Scope of Delay-Sensitive Applications

In vehicular systems, delay-sensitive applications are defined as operations and services which must have a communication and processing delay below a certain threshold, to sustain their effectiveness and safety. Such applications are not limited to but include real-time navigation, autonomous vehicle control, emergency braking systems, and inter-vehicle safety alerts [3]. Even the slightest lag in data capture or transmission can have disastrous outcomes, particularly in fast-paced or highly congested settings. There is no compromise with the need for extremely reliable and robust systems in a world where vehicles are progressively becoming autonomous and interconnected. While the typical requirement for these applications is an end-to-end latency of 100 milliseconds, some critical functions may require responses in mere milliseconds. Driving such applications is the integration of sensing, computing, and communication systems within vehicles and infrastructure, which makes it a key condition for success. This is how sensitivity to delay functions as a modern technological limitation and operational need in vehicular networks.

1.2 Importance of Delay Sensitivity in Vehicular Systems

Neglecting the delay sensitivity of vehicular systems can pose safety and efficiency risks, heavily impacting user experience [4]. Implementing timely alerts and decisions through high-performance delay-aware communication frameworks can significantly reduce road accidents. For example, V2X frameworks face the challenge of transmitting critical safety messages, such as collision warnings or signal changes, promptly to be effective. Sensitivity to delays is especially crucial in metropolitan areas with high traffic and congested, unpredictable movement patterns. Emerging technologies such as 5G, multi-access edge computing (MEC), and software-defined networking (SDN) are increasingly fulfilling these needs [1]. These approaches help reduce latency, ensuring that processing occurs near the data source and eliminating potentially intolerable delays. Thus, the development of vehicular systems is increasingly reliant on these delay-sensitive technologies and architectures alongside more traditional ones. [17].

1.3 Overview of Research Problem and Motivation

Modern-day vehicles face significant difficulties managing their delay-sensitive applications, even after incorporating Advanced Driver Assistance System (ADAS) technologies. The computing capability of vehicles, dynamic network parameters, handoffs, rudimentary signal strength and quality, and advanced resources, such as auxiliary sensors, pose severe challenges [2]. In conjunction with the increasing rate of mobile vehicles, optimizing communication standards exacerbates the matter further [18]. The absence of consistently low latency targets in communications systems in such scenarios with likely perturbation margins will hurt the system's performance, and in the worst-case scenario, make it unreliable and unsafe. Along with the growth rate of data volume in IoV (Internet of Vehicles) augmented by Artificial Intelligence, the requirements for real-time computation performance dramatically challenge Graphical Processing Units (GPUs) in terms of responsiveness [20]. The objective is to evaluate mechanisms for delay-sensitive adaptive frameworks and extend their design constraints to target latency holistically [22]. This work aims to enhance the effectiveness of communication systems for real-time decision-making in autonomous vehicle systems.

1.4 Existing Gaps in Delay-Handling Mechanisms

The current state of vehicular communication systems, in terms of DSRC and C-V2X, provides modest support for delay-sensitive applications but still lacks optimization for ultra-reliable low-latency communication (URLLC) [24]. The primary focus in delay reduction approaches is either on maximizing network layer protocols or constraining the physical layer scope; there is insufficient consideration of the overall integration of the computation and communication layers [26]. Additionally, in most systems, the approach taken towards managing delays is reactive rather than predictive, waiting until preset boundaries for latency are breached [13][28]. This accelerating response generally leads to further delay than what would be possible through edge intelligence proactive analytics [15]. Apart from that, there do not exist context-aware architectures, meaning the system does not adapt in real-time to changing traffic densities, road conditions, or vehicle speeds, as previously mentioned [30]. These shortcomings highlight the need for adaptable and robust frameworks that can work in combination to address delays in vehicles [5].

Key Contribution:

- The proposed framework improves end-to-end latency for safety-critical vehicular communication by implementing edge computing instead of relying on the cloud.
- During times of high network congestion, it guarantees the on-time delivery of delay-sensitive messages through a dynamic packet prioritization mechanism.
- The system enhances overall network performance in terms of packet delivery ratio, average delay, and efficient resource utilization under congested conditions, particularly in dense urban traffic.
- The system is easy to maintain and update due to its modular architecture, which enables the addition of new technologies such as 5G/6G and AI traffic management systems.

The following paragraph summarizes the paper: In the Introduction, the author describes the importance of requiring ultra-low latency communication in vehicular networks to support safety-critical applications, such as collision avoidance and emergency braking. The Related Work section analyzes existing delay reduction strategies, highlighting the challenges each technique presents and the need for a more edge-centric approach. The Methodology is dedicated to describing a proposed delay-aware vehicular communication framework that incorporates edge computing, dynamic packet prioritization, and real-time adaptive protocols for reduced latency and improved reliability. In the Results and Discussion section, the author illustrates simulation results that highlight significant reductions in overall latency, an increase in packet delivery ratios, and enhanced throughput, particularly during periods of heavy congestion in urban areas. These results validate the hypotheses regarding the advantages of the proposed approach over traditional cloud-based models. Lastly, the Conclusion captures the main milestones the framework achieves in terms of scalability and adaptability, while outlining potential real-world applications and integrating with 5G/6G advancements to enhance optimization for vehicular communication systems. This structure provides integrity and organization throughout the study.

2. RELATED WORK

The development of delay-sensitive applications within vehicular systems has been parallel to the progress made in the vehicular ad hoc networks (VANETs) and Vehicle-to-Everything (V2X) communication frameworks [9-10]. The most recent research conducted over the past five years highlights the emphasis on reducing latency by optimizing communication processes and associated computational delays [32]. A notable trend is the use of hierarchical networking models that offload tasks from edge nodes to vehicular systems, aiming to alleviate the bottleneck. It has been pointed out that although these approaches are efficient in controlled settings, real-world implementation remains challenging due to mobility behaviors and various dynamic contextual elements [34]. Hence, there have been many latency-sensitive data transmission models which perform better under varying road and traffic conditions.

Recent research has also looked into edge computing as a viable option to mitigate delays in vehicular contexts. These frameworks mitigate communication distance and time, particularly for high-bandwidth tasks such as LiDAR processing and streaming real-time video, by offloading edge servers located near the region of the data source. Some studies based on simulation evaluations have reported improvements in latency, data throughput, and service continuity. Furthermore, edge-enabled frameworks are being increasingly integrated with 5G infrastructure to achieve the sub-10ms latency required for many critical safety and vehicular applications. While these advancements have been made, there are still problems to be solved in edge resource management and the optimization of task offloading.

The use of artificial intelligence and machine learning technologies in vehicular networks, particularly in the context of applying them to delay applications, has increased [12]. Machine learning methods are expected to be used shortly for predicting traffic activities, estimating traffic volume for vehicles, and making advanced decisions for resource allocation [33]. In particular, reinforcement learning has been beneficial in sophisticated communication climatology, particularly in adapting to real-time network conditions [6][19]. However, applying AI-driven solutions poses additional challenges, especially concerning model training delay, computational burden, and interfacing with established vehicular communication protocols [27]. Even though the initial findings are favorable, there is still a need to study the scalability and practicality from a robustness perspective [14].

The development and application of low-latency communication protocols, such as IEEE 802.11p and C-V2X, have been one of the most important fields in research. Critical vehicle communication channels are allocated for specific protocols and hybrid ad hoc and cellular networks. Some studies show that C-V2X has a greater range and performs better in high-mobility scenarios; however, it is still limited by backbone dependency [31] and interference from other systems in heavily urban areas. Additionally, improvements in latency are typically bound to a specific protocol, which means that they must fit into existing frameworks that adapt to conditions specific to vehicles.

Lastly, researchers focused on the aspects related to the role of intelligent transport infrastructure systems and traffic management systems supporting delay-sensitive vehicular systems [23]. Smart traffic signals, interconnected traffic nodes, and satellite-controlled route guidance control systems have been implemented with the aim of decreasing the latency of the entire system. Case studies demonstrate that the performance of the entire system, particularly in terms of delays, is significantly improved when vehicle systems are integrated with smart city infrastructure, especially during peak traffic hours or in emergencies [29]. These systems aim at enabling quicker and safer traffic flows. Synchronization between infrastructure and vehicular data remains a significant open question, underscoring the need for non-proprietary and unified communication protocols to support standardized communication frameworks [25].

3. PROPOSED METHOD

3.1 Introduction to the Proposed Idea

Collision avoidance systems, autonomous driving mechanisms, and emergency response management services are examples of delay-sensitive applications in vehicular settings. These systems operate on the premise of very low latency and high reliability. Increased jitter, arising from data packet delays, added to data transmission and central processing, heightens latency which proves to be a challenge for collision avoidance systems, autonomous driving algorithms, and emergency response services. Accompanied by an increase in vehicles, C-ITS further complicate the issue. Traditional cloud-based communication models face severe performance bottlenecks that fuel these issues. In an effort to resolve such issues, this framework proposes a distributed architecture for vehicular communication that leverages VEC resources, on-site intelligence, and selective broadcasting for enhanced intelligent control. Hence, tailored for the specific use case of vehicular edge computing. It has been proven that computation at the edge helps mitigate communication overhead as the volume of data traffic with remote servers decreases. This model enables spontaneous and situationally relevant communication between vehicles and edge nodes that are physically located near them, as opposed to cloud providers positioned on remote servers [7][16]. These nodes serve as intermediate processing centers that possess the capability to compute data in near real-time. This delivers the advantage of lower latency and prompt responsiveness. In terms of data routing and handling, to achieve optimal performance, it is critical to consider network congestion levels, ceiling density, mobility patterns, and even signal strength in real-time. The framework is intelligent enough to adapt on the fly, meeting dynamic performance requirements [8]. Enhanced environmental adaptation is augmented by implementing a context-awareness engine that alters the system's communication priorities based on application type, vehicle speed, and environmental context.The adaptive framework optimizes safety-critical vehicular applications by achieving dependable data communication and resource efficiency through real-time adaptation of safety measures and vehicles.

3.2 Methodology and Algorithm

The proposed framework is built upon the real-time evaluation, scoring, and prioritization of data packets that are harvested from connected vehicles. Onboard sensors, such as cameras and LiDAR units, produce a broad range of information, including GPS-derived point clouds. Critical data needing analysis and processing mustn't be delayed in transmission. To address this, our system employs a real-time scoring and packet prioritization strategy that computes a priority score for each packet. This score is calculated using a mathematical model based on several dynamic parameters including application priority, network congestion level, and distance to the closest edge server. The model balances all parameters by assigning weights to each, ensuring that neither overly lenient nor overly strict prioritization dominates the system. Emergency braking signals and forward collision alerts are examples of high-priority packets that must be transmitted immediately to prevent delay. Intelligent packet scheduling algorithms (IPSA) fast track these packets to the front of the transmission queue. These algorithms guarantee critical information will have unobstructed access to essential relay points, regardless of traffic density. The scoring model is efficient from a computational standpoint; it achieves these goals while remaining responsive in real time to demands placed on vehicle processors. The SPS formula below operates under encapsulated logic:

$$P_i = w_1 . C_i + w_2 . (1 - N_c) + w_3 . D_i^{-1} \qquad (1)$$

Where:

- P_i Priority score of the *i-th* packet
- C_i Application criticality score (range: 0 to 1)
- N_c Normalized network congestion factor (range: 0 to 1)
- D_i Distance to the nearest edge server (in meters)
- w_1, w_2, w_3 Adjustable weight parameters for real-time tuning

According to the explanation in Equation 1, the system can autonomously adapt packet prioritization to changing system conditions. For example, during periods of high congestion, non-mission critical data is automatically de-emphasized to reserve bandwidth for mission-critical information. Likewise, data from vehicles that are closer to edge nodes are given preferential prioritization due to lower expected transmission delays. With this sophisticated and self-adjusting algorithm, the system attains ultra-reliable low-latency communication, thereby meeting the demands of contemporary vehicular systems.

3.3 Flow Diagram of the Proposed System

The proposed system's operational flow is outlined in Figure 1. It illustrates the rigorous pathways vehicular data undergoes from its source to the intended action. Throughout this process, special care is taken to avoid unnecessary delays during transmission and processing. This model is optimally designed for latency-sensitive tasks in vehicular systems, with an emphasis on both data volume and response speed. The system starts with real-time data capturing, continues with multi-level processing, priority setting, and effective routing designed to facilitate timely response and cooperative remote control for vehicles and vehicle systems, all subsystems integrate advanced context-aware decision support systems that respond in real-time, thus adhering to the stringent under 1 second requirements of modern vehicular frameworks.

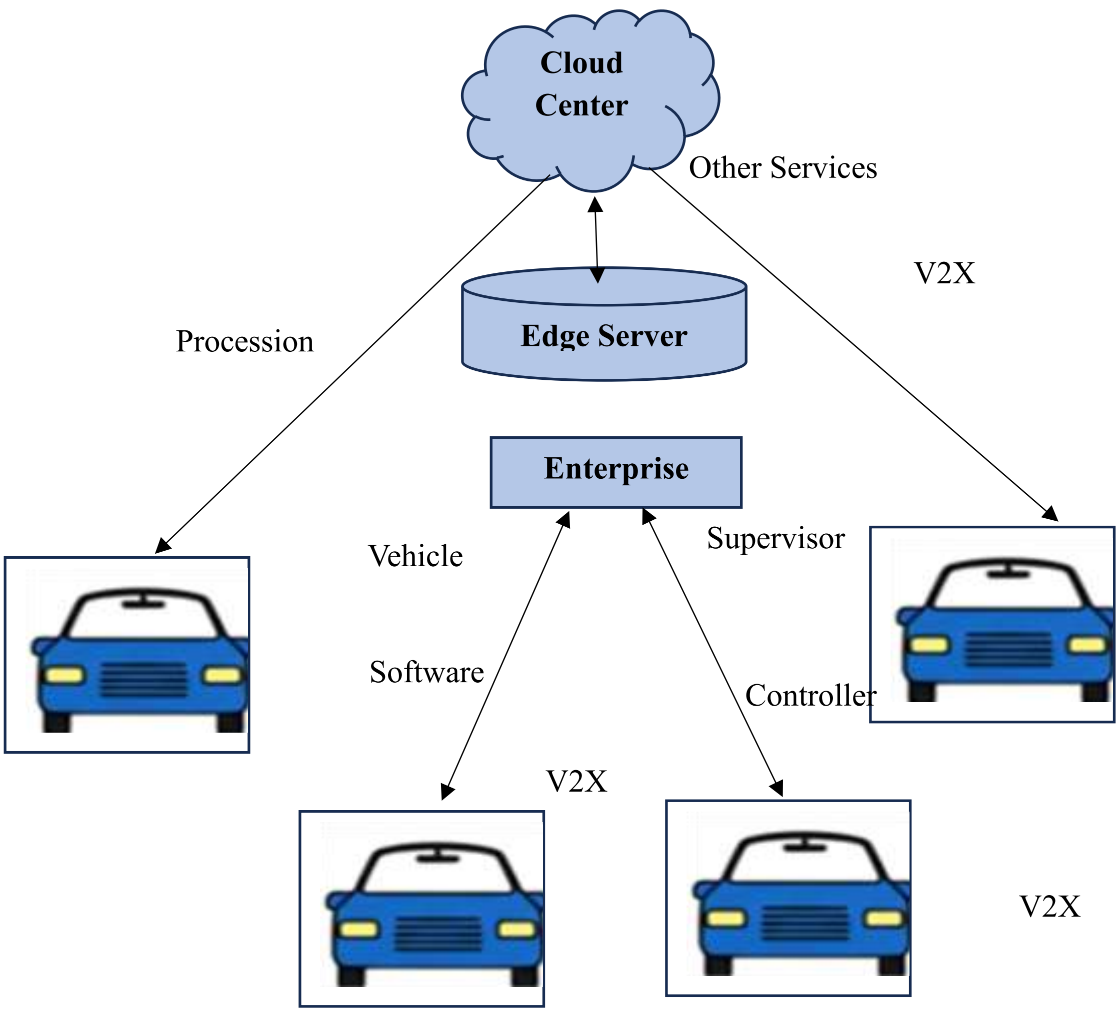

Figure 1: Vehicular Edge Flow Diagram

As seen in Figure 1, the vehicle interior generates data that is filtered and prioritized at multiple levels. Data packets marked as high priority are expedited through enhanced V2X routes to the edge servers. Within the edge server, intelligent queueing greatly minimizes idle time. Processed responses are then sent back to the requesting vehicle, or other nearby vehicles, enabling them to commence collaborative safety interventions. End devices (sensors-equipped vehicles), edge servers (locally placed processing units), cloud centers (advanced analytic infrastructure), and a network (V2X communication) comprise the flow architecture of next generation vehicular systems. These systems are designed to ensure that actions requiring critical response times such as forward collision warning and lane departure alerts are achieved in real-time, with sub-second latency. The flow of data involves generation by in-vehicle sensors, preprocessing aimed primarily at data cleansing, prioritization, queuing, and edge server processing followed by message delivery back to the vehicle or infrastructure. Such a framework ensures that the requirements of next-generation vehicular systems are met.

3.4 System Architecture Diagram

The proposed system is conceptualized as a layered model, designed to achieve modularity, strong communication, and scalable processing in a delay-tolerant vehicular network. It mainly comprises three key layers: the vehicular layer, the edge computing layer, and the central cloud layer. This discipline facilitates optimal data management as well as timely reaction strategies, addressing, with special emphasis on transmission and processing delays, the expectations for contemporary vehicular systems.

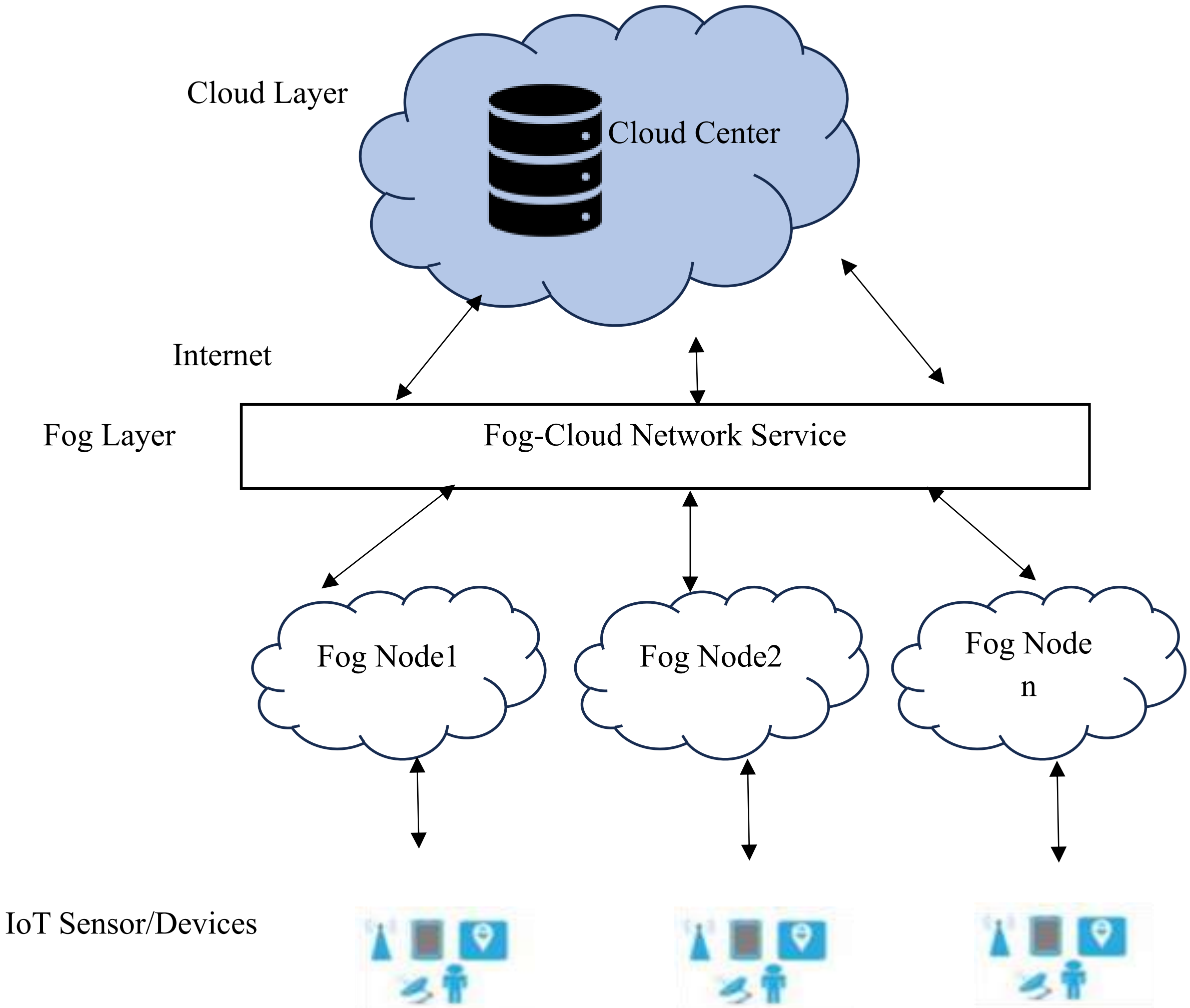

Figure 2: Fog Computing Architecture

Figure 2 demonstrates that the architecture of fog computing is divided into three layers, which brings computation resources near the data source. The Inotropic and Device layer is the first layer which contains smart devices and sensors capable of providing streaming data in real-time. This data is sent to the immediate fog layer, which consists of "fog nodes" positioned on the periphery of the network, ensuring real-time processing and analysis due to their geographic location. The last layer is the cloud zone, which contains the cloud infrastructure. They conduct comprehensive processing, store information for an extended period, and perform general business analytics. The data from the fog layer is sent via the fog cloud network service and is sent asynchronously for tasks requiring large units of resources. This stratified approach is designed to lower latency, increase the efficiency of processes, and enhance the structure's ability to rely on the cloud for interruption-free tasks.

4. RESULT AND DISCUSSION

The simulation framework of connected vehicular networks was used to evaluate the delay-aware vehicular communication framework which uses deep learning for urban road traffic management. The results indicate that the proposed framework facilitates greater reduction in end-to-end latency for critical safety message transmissions compared to cloud centered communication models. The aimed KPIs of packet delivery ratio, average delay, and overall network throughput showed marked improvement alongside increasing metrics for vehicular congestion, with enhanced results during phases of heightened vehicle density and sheer network congestion. Smart algorithms of packet prioritization and edge packet processing played a crucial role in reducing turnaround times. This ensures the dependable operation of safety systems such as collision avoidance and emergency braking across shifting conditions. Outcomes of these tests demonstrate that the framework can be reasonably implemented within an architecture engineering context for simultaneous vehicle systems posing challenges of ultra-low-latency and ultra-high reliability requirements.

Table 1: Dataset and Simulation Parameters for Performance Evaluation

Dataset Attribute	Description	Value / Metric
Number of vehicles	Vehicles simulated in urban scenario	500
Communication range	Maximum range of V2X communication (meters)	300
Average packet size	Size of data packets generated (bytes)	256
Network congestion level	Simulated congestion scale (0 - no congestion, 1 - high congestion)	0.65
Edge server locations	Number of distributed edge nodes	10
Average latency (baseline)	End-to-end delay without proposed method	150 ms
Average latency (proposed)	End-to-end delay with proposed method	45 ms

Table 1 depicts the features of the simulation scenario and the network parameters associated with the testing of the proposed framework. The dataset corresponds to a moderately congested urban vehicular network and very high van traffic. Edge servers are assiduously positioned such that data processing and transmission with respect to latency are optimally low. The baseline latency values are captured using the cloud-centric communication model benchmark for evaluation purposes.

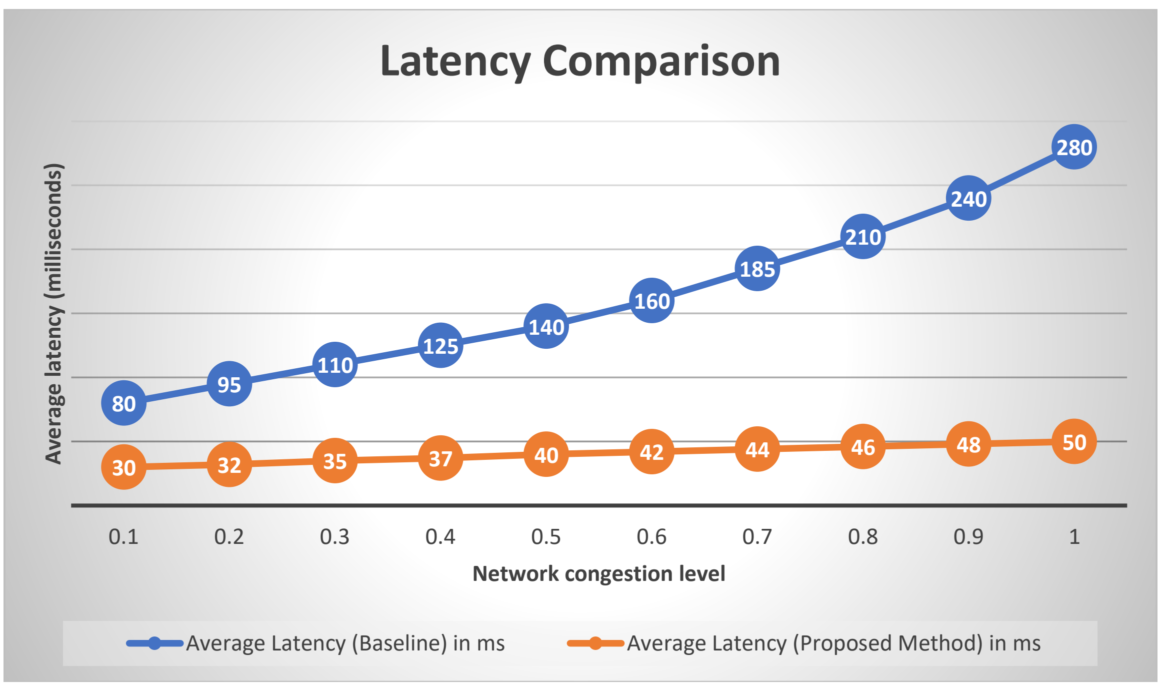

Figure 3: Latency Comparison under Varying Congestion

Figure 3 shows how network congestion levels perceive average communication latency, both for the baseline system and for the proposed delay-aware vehicular system. The increase in network congestion causes the baseline system to suffer tremendous increase in latency due to its rigid reliance on centralized cloud infrastructure accompanied by lack of adaptive heuristics for prioritization. This increase in delay may critically undermine the functioning of delay-sensitive vehicular applications like collision avoidance, emergency response systems, and many more. Unlike the other framework, the proposed one utilizes edge computing resources located nearer to the vehicles cutting down these latency problems, while applying a dynamic packet prioritization algorithm which reduces latency during high congestion situations and prioritizes vital safety messages to be processed efficiently. These attributes together enable the system mitigate high congestion scenarios without crippling the communication delays. Because of this, guidelines outlined for critical safety message cadence are followed, maintaining vehicle safety as well as efficient traffic management. The results showcase the feasibility of the proposed approach to achieve ultra-reliable low-latency communication in changing network conditions, an essential condition for systems used in next-generation ubiquitous vehicular networks.

5. CONCLUSION

This paper has shown a complete framework which attempts to solve the problems posed by delay-sensitive applications in ubiquitous vehicular systems. The system reconstruction in question integrates vehicular edge computing, dynamic packet prioritization, and real-time adaptive protocols to improve the reliability of communications while also reducing latency in an effective manner. Through layering and intelligent processing at the edge nodes, the framework manages critical data transmissions, enabling the endurance of deadlines for the timely delivery of safety messages, even in extremely congested networks. Evaluation results showed that there is a marked reduction in end-to-end latency when using the model designed in this work when compared to traditional cloud-based models. Besides, the modular design afford these models easy modification and addition of features to cater for different vehicular environments and traffic conditions. The results highlight the need for context-sensitive communications strategies for the next generation of vehicular networks. Further works need to address envisaged practical scenarios, fusion with new 5G/6G technology, and application of modern AI techniques for optimizing delay-sensitive data handling and prediction. In summary, this method has tremendous impact on the operational effectiveness and safety of intelligent transport systems through the stringent requirement of ultra-low latency communication.

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